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Assessment of contribution of Australia's energy production to CO_2 emissions and environmental degradation using statistical dynamic approach

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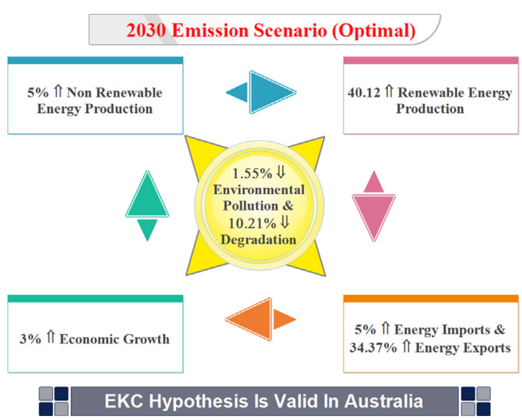
HIGHLIGHTS

- The study validates the Environmental Kuznets curve hypothesis.
- Environmental pollution depends on the share of disaggregate energy sources.
- Renewable energy plays a vital role in environmental sustainability.
- Structural change in economic growth is critical to climate change mitigation.
- Emission reduction target can be met by reducing fossil fuels and energy imports.

GRAPHICAL ABSTRACT



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ABSTRACT

Energy production remains the major emitter of atmospheric emissions, thus, in accordance with Australia's Emissions Projections by 2030, this study analyzed the impact of Australia's energy portfolio on environmental degradation and CO_2 emissions using locally compiled data on disaggregate energy production, energy imports and exports spanning from 1974 to 2013. This study employed the fully modified ordinary least squares, dynamic ordinary least squares, and canonical cointegrating regression estimators; statistically inspired modification of partial least squares regression analysis with a subsequent sustainability sensitivity analysis. The validity of the environmental Kuznets curve hypothesis proposes a paradigm shift from energy-intensive and carbon-intensive industries to less-energy-intensive and green energy industries and its related services, leading to a structural change in the economy. Thus, decoupling energy services provide better interpretation of the role of the energy sector portfolio in environmental degradation and CO_2 emissions assessment. The sensitivity analysis revealed that nonrenewable energy production above 10% and energy imports above 5% will dampen the goals for the 2030 emission reduction target. Increasing the share of renewable energy penetration in the energy portfolio decreases the level of CO_2 emissions, while increasing the share of non-renewable energy sources in the energy mix increases the level of atmospheric emissions, thus increasing climate change and their impacts.

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1. Introduction

Mitigating climate change and its impact while ensuring access to affordable modern energy has become a global challenge. The availability, accessibility and utilization of energy play a critical role in modern economic growth. Economic productivity is powered by energy production and consumption, a situation that distinguishes developed, developing and least developed countries. Energy drives almost all the sustainable development goals, ranging from poverty eradication, wellbeing, jobs and economic growth, food and water supply, industrialization, responsible production and consumption, and climate change mitigation (Owusu and Asumadu-Sarkodie, 2016; United Nations, 2015). However, the adverse effect of energy production and consumption on environmental pollution and degradation requires an empirical investigation.

There is a pool of studies on the role played by economic development in the acceleration of environmental pollution. The seminal work of Grossman and Krueger (Grossman and Krueger, 1991) on environmental Kuznets curve (EKC) hypothesis motivated the modern research on environmental pollution-economic growth nexus. The notion of EKC hypothesis supports the "*grow first clean later*" development strategy which postulates that the initial stages of economic development through industrialization and urban growth increases the consumption of natural resources to meet the growing demand, thus depleting the biocapacity leading to the ecological deficit and environmental deterioration.

The aftermath of Grossman and Krueger's work has motivated several studies on EKC hypothesis using both time series and panel data techniques, however, there are limited studies available in testing the EKC hypothesis in Australia. For example, Balaguer and Cantavella (2018) examined the role of education in Australia's EKC hypothesis with an autoregressive distributed lag approach from 1950 to 2014. The study revealed that education has a potential effect on environmental pollution contrary to economic growth in environmental policy formulation and implementation. Stern (2017) investigated adequacy of the EKC hypothesis model in Australia after 25 years and concluded that economic growth contributes to Australia's environmental pollution. The robustness of the econometric method was found to play a vital role. Similarly, Moosa (2017) examined the validity of the EKC hypothesis in Australia and found that without proper econometric method, the validity of the EKC hypothesis is rejected. The use of sensitivity analysis which validates the existence of EKC hypothesis in Australia was proposed. Shahbaz et al. (2017) found a long-run equilibrium relationship between energy consumption, population growth and globalization with environmental pollution. Their study confirmed a unidirectional causality from energy consumption to environmental pollution. It appears that none of the studies in Australia examined the role of energy sector dynamics on CO_2 emissions and degradation.

The relationship between economic growth, CO_2 emissions and energy consumption has been a subject of a number of studies summarized in Appendix A. These studies can be divided into three categories, namely the pollution-economic growth nexus, the pollution-energy-growth nexus, and the pollution-energy dynamics-growth nexus. The relationship between economic growth and environmental pollution produces two-sides for policymakers which is vital in developing the economies. As much as governments want to grow their economy without limitations, the other constraint is maintaining environmental sustainability, which has become a global target. Many studies have confirmed that the economic development has a positive monotonic relationship with environmental pollution (Acaravci and Ozturk, 2010; Narayan and Narayan, 2010; Saboori et al., 2016; Sarkodie and Owusu, 2016a; Sarkodie and Owusu, 2016b). The scale effect can be examined by using the EKC hypothesis pathway or the direction of causality in the pollution-economic growth nexus.

Beside the scale effect, many studies on the pollution-economic growth nexus either follow the growth hypothesis, conservation hypothesis, neutrality hypothesis or the feedback hypothesis. The growth hypothesis postulates that the direction of causality moves from environmental pollution to economic development but not vice versa, meaning that policy implementations that propel environmental quality will affect economic growth (Bastola and Sapkota, 2015). The conservation hypothesis postulates that environmental quality depends on economic growth, meaning that environmental sustainability options, such as carbon capture and sequestration technologies in carbon-intensive resources, afforestation, etc. can only be driven by wealth and willingness to pay for a quality environment. In this case, the conservation hypothesis supports the EKC hypothesis, but only economic reliant countries can be in this category. For instance, as part of Australia's Emissions Projections by 2030, measures have been instituted to reduce deforestation compared to historical trends (Commonwealth of Australia, 2016). Several studies confirm the unidirectional causality running from economic growth to environmental pollution (Sarkodie and Owusu, 2016c). The neutrality hypothesis suggests no relationship between environmental pollution and economic growth. Improving economic growth has no effect on environmental quality. The feedback hypothesis suggests that the nexus between environmental pollution and economic growth is complimentary. Accordingly, there is a bi-directional causality between economic development and environmental quality and vice versa (Chang, 2010; Sarkodie and Owusu, 2017b).

The second strand of studies focuses on the pollution-energy-growth nexus. The role of energy consumption and economic development cannot be underestimated in environmental pollution and sustainability. A decline in the trend of energy consumption in relation to economic development indicates that a country's economy can improve its energy efficiency (Chiu, 2017; Salahuddin and Gow, 2014).

The final strand of studies focuses on the pollution-energy dynamics-growth nexus. The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report reveals that provision of energy services or energy consumption in the form of heat and electricity is the highest contributor to greenhouse gas emissions compared to agriculture, forestry and land-use, transportation, and others (IPCC, 2016). The IPCC data reveal that fossil fuel energy generation in 2010 remained the highest contributor of carbon dioxide emissions with 39% increase in concentrations above the pre-industrial levels (IPCC, 2011).

The investigation of existing literature reveals the evidence of the role of energy consumption (aggregate or disaggregate) and economic growth on environmental pollution. However, there are several identified limitations in the current state of knowledge, as outlined below:

- The existing literature reveals a mixed outcome on the role of energy consumption and economic growth on environmental pollution, depending on the econometric method, the country of the study, the duration of the data and the source of data.
- Most of the reviewed studies employ synthetic data rather than locally compiled data which provides the true account of the trend exhibited by the data series.
- Most of the employed econometric methods, such as fully modified ordinary least squares (FMOLS), dynamic ordinary least squares (DOLS), autoregressive distributed lag (ARDL), vector error correction model (VECM), and vector autoregressive (VAR) for single countries are unable to reveal the variable importance and eliminate multicollinearity, which is problematic in energy-growth-pollution nexus reported in several studies.
- Majority of literature focuses on aggregate energy consumption rather than disaggregate energy consumption.
- To the best of our knowledge, none of the studies under consideration examined the role of disaggregate energy production in sustainable development.

- None of the reviewed literature considers the role of energy services such as energy imports and exports, which are critical for assessment of environmental pollution and sustainable development. According to the IPCC (2011) Fifth Assessment Report on renewable energy and climate change, the share of imports in the total primary energy consumption, energy imports and exports are critical indicators for the assessment of energy security in sustainable development.

The study aims to contribute to furthering the existing knowledge by, first, using locally compiled data inventory on energy and its related services to ascertain the real evidence of the role of disaggregate energy production, energy imports, energy exports and economic development in environmental pollution and degradation in Australia. Secondly, this study employs the statistically inspired modification of partial least squares capable of eliminating multicollinearity problems reported in previous literature. This method reveals the significance of data series prior to model estimation, which is absent in other econometric methods like autoregressive distributed lag, fully modified and dynamic ordinary least squares regression, and among others reported in the literature. Third, this study undertakes sustainability sensitivity analysis capable of estimating how environmental pollution and degradation can be minimized while increasing economic development and energy security. Finally, this study reveals the structural implications of the environmental pollution and degradation using the environmental Kuznets curve hypothesis that stimulates policy implication and provides information and policy guidance to help Australia's transformation towards achieving the Sustainable Development Goals by 2030.

Based on the economy-wide emission reduction targets by the Annex I parties in the climate change convention, Australia is expected to reduce its emissions by 5–15% by 2020 compared to the 2000 levels, to stabilize greenhouse gas concentrations at 450 ppm in the atmosphere (Secretariat, 2014). This study in accordance with Australia's Emissions Projections by 2030, focuses on Australia to examine how its energy portfolio contributes to CO_2 emissions and environmental degradation through modern econometric methods and provide a sensitivity analysis on how adjustments can be made towards the achievement of a decarbonized economy while meeting the emission targets.

2. Methods

To examine the environmental impacts of Australia's energy portfolio, this study employs data on carbon dioxide emissions [CO_2, (kt)] and economic growth per capita [RGDP, (current LCU)] from the World Bank (2016b) Development Indicators, data series on ecological footprint [EF, (Consumption per capita)] adopted from the Global Footprint Network (2017b) while data on renewable energy [RENE, (Petajoules)], nonrenewable energy [NRENE, (Petajoules)], energy imports [ENEE, (Petajoules)] and exports [ENEI, (Petajoules)] are derived from the Department of Industry Innovation and Science (2016) data on energy. Ecological footprint is defined as, "a measure of how much area of biologically productive land and water an individual, population, or activity requires to produce all the resources it consumes and to absorb the waste it generates, using prevailing technology and resource management practices" (Global Footprint Network, 2017a). In this study, ecological footprint is represented as a proxy for environmental degradation, as recommended by Al-Mulali et al. (2015). Table 1 presents the variables and data series description used in this study. The data series on renewable energy comprises of biomass (wood, wood waste, bagasse, and other waste), biogas, biofuels (ethanol and biodiesel), hydropower, wind, solar photovoltaics (PV) and solar water heater. Nonrenewable energy comprises of oil, natural gas, brown coal and black coal. Energy exports include coal, natural gas, refined products, liquid petroleum gas and crude oil. Energy imports include coke, natural gas, refined products, liquid petroleum gas and crude oil.

Table 1
Data description.

Variable	Description	Unit
EF	Ecological Footprint	Consumption per capita
NRENE	Nonrenewable	Petajoules
RENE	Renewables	Petajoules
ENEE	Energy Exports	Petajoules
ENEI	Energy Imports	Petajoules
RGDP	GDP per capita	current LCU
CO2	CO2 emissions	kt

This study adopted disaggregate energy production rather than aggregate energy consumption presented in previous studies, to investigate the Australian energy sector dynamics, because Australia's energy consumption embodies national energy production and energy imports for energy conversion activities which include petroleum refining and electricity generation among others, and excludes fuels supplied to ships and aircraft for international transportation. Decoupling energy services, such as energy imports, provides better interpretation to the role of energy-related services in assessment of environmental degradation and CO_2 emissions. On the other hand, energy production entails energy produced prior to energy consumption, conversion or transformation and related losses before utilization.

The relationship between ecological footprint (*EF*) and carbon dioxide emissions (CO_2) as dependent variables versus nonrenewable energy (*NRENE*), renewable energy (*RENE*), per capita (*RGDP*), squared of per GDP ($RGDP^2$), energy imports (*ENEI*), energy exports (*ENEE*) can be expressed as:

$$CO_2 = f(RENE, NRENE, RGDP, ENEE, ENEI) \tag{1}$$

$$CO_2/EF = f\left(RENE, NRENE, RGDP, RGDP^2, ENEE, ENEI\right) \tag{2}$$

The empirical specification of Eq. (1) follows the fully-modified ordinary least squares (FMOLS), dynamic ordinary least squares (DOLS) and canonical cointegrating regression (CCR) pathway expressed as:

$$CO_{2t} = \beta_0 + \beta_1 RENE_t + \beta_2 NRENE_t + \beta_3 RGDP_t + \beta_4 ENEE_t + \beta_5 ENEI_t + \varepsilon_t \tag{3}$$

where β_0 denotes the intercept, $\beta_1, \ldots, \beta_5$ denote the slope coefficients, and ε denotes the error term at time t.

To estimate the FMOLS regression, this study employs the FMOLS estimator by Phillips and Hansen (1990) expressed as:

$$\hat{\theta} = \begin{bmatrix} \beta \\ \hat{\gamma}_1 \end{bmatrix} = \left\langle \sum_{t=2}^{T} Z_t Z_t' \right\rangle^{-1} \left\langle \sum_{t=2}^{T} Z_t\, y_t^{+} - T \begin{bmatrix} \lambda_{12}^{+} \\ 0 \end{bmatrix} \right\rangle \tag{4}$$

To estimate the CCR, this study employs the CCR estimator by Park (1992) expressed as:

$$\hat{\theta} = \begin{bmatrix} \beta \\ \hat{\gamma}_1 \end{bmatrix} = \left\langle \sum_{t=1}^{T} Z_t^{*} Z_t^{*\prime} \right\rangle^{-1} \sum_{t=1}^{T} Z_t^{*} y_t^{*} \tag{5}$$

where β cointegrating equation coefficient, $\lambda_1^{+}{}_2$ is the estimated bias correction term, X_t is the levels regression, y_t^{+} is the modified dependent variable, $Z_t = (X_t', D_t')'$ for FMOLS, $Z_t^{*} = (Z_t^{*\prime}, D_1{}_t')'$ for CCR denotes the regressors, D denotes the deterministic trend, at sample size T and time t. FMOLS is based on a semi-parametric correction, thus, the FMOLS estimator is based on symmetric and one sided long-run covariance matrices of the residuals necessary to eliminate the challenges associated with the cointegrating equation and the stochastic regressor innovations in a long-run correlation (Phillips and Hansen, 1990). On the contrary, the CCR estimator eliminates the challenges associated with the cointegrating equation and the stochastic regressor innovations in a long-run correlation using the least squares of the stationary transformed data series (Park, 1992).

To estimate the DOLS regression, this study employs the DOLS estimator by Saikkonen (1992); Stock and Watson (1993) expressed as:

$$y_t = X_t\beta + D_1\gamma_1 + \sum_{j=-q}^{\tau} \Delta X'_{t+j}\delta + v_{1\,t} \tag{6}$$

where y is the dependent variables, X denotes the cointegrating independent variables, β long-run cointegrating equation coefficient, D denotes the deterministic trend, δ denotes the short-run dynamic coefficient, Δ denotes the difference operator, τ denotes the leads, q denotes the lags, v denotes the residual variance at time t. The advantage of using the DOLS estimator is to eliminate the feedback mechanism evident in the cointegrating system through the augmentation of the cointegration regression with lags and leads resulting in an orthogonal error term of the cointegrating equation thus, making it an efficient estimator (Saikkonen, 1992; Stock and Watson, 1993).

To fulfill the requirements of the FMOLS, DOLS, and CCR, this study first tests the cointegration between data series using the Hansen's Instability Test (Hansen, 1992) based on the null hypothesis of cointegration, thus a fulfillment of this condition means there is evidence of parameter stability.

The FMOLS and CCR estimator adjusted the sample to 1975–2013 and employed a constant as the cointegrating equation deterministic while regressor equations were estimated using differences. On the contrary, the DOLS estimator adjusted the sample to 1975–2010 and employed constant and trend as the cointegrating equation deterministic with fixed leads of three and zero lags specification. However, all the three estimators employed Prewhitening with three lags from an automatic selection using Akaike Information Criterion at a maximum of three lags and Bartlett kernel, Integer Newey-West of 4 fixed bandwidths for the long-run covariance estimation. It is important to note that the squared of per capita GDP in these models was excluded due to issues with collinearity.

The partial least squares (PLS) regression is a multivariate method with a range of advantages over the principal component analysis because the PLS is insensitive to the usual multicollinearity between independent variables. Importantly, the PLS reveals the variable importance of projection of data series, which is a disadvantage of the econometric methods (Samuel and Owusu, 2017). Moreover, PLS prediction is better than the principal component analysis and econometric methods but not with the neural network (Sarkodie and Owusu, 2016c) using Monte Carlo Simulation. The PLS model assumes that the causal relationship is driven by linear combinations of observed predictor variables known as latent variables or factors. The main aim of the PLS is to produce score values from few eigenvectors of the predictor variables, which are summarized in the variance of the predictor variables that are highly correlated with the dependent variables. For brevity, the PLS model consists of both the outer relation and the inner relation. The former results from the decomposition of the eigenstructure X and Y matrices while, the later links the scores for X and Y matrices through a regression expressed as:

$$X = TP^T + E \tag{7}$$

$$Y = UQ^T + F \tag{8}$$

$$U = BT \tag{9}$$

where X is an $n \times m$ matrix of the predictors, Y is an $n \times p$ matrix of the responses, n denotes the samples, m and p denote the variables, T and U are $n \times l$ matrices which represent projections of X and Y ($-$scores), P and Q are $l \times m$ orthogonal loading matrices, P^T and Q^T denote the transposed P and Q matrices, E ($n \times m$ matrices) and F ($n \times p$ matrices) represent the error term, while, B is the regression coefficient with $n \times n$ matrices. The relation of X is achieved by the decomposition of X into T (scores) and P (loadings) matrices as shown in Eq. (7). The relation of Y is achieved by decomposition of Y into U (scores) and Q (loadings) matrices as shown in Eq. (8). Thus, the aim of the PLS model is to reduce the norm of F residual matrix while still achieving a correlation between X and Y. However, the inner relation of Eq. (9) is weak, thus requires a better algorithm that increases the predictive power of the response variable. Literature shows that the statistically inspired modification of partial least squares (SIMPLS) is superior to PLS (Li, 2006) or the non-linear iterative partial least squares (Sarkodie and Owusu, 2017a). The empirical specification of Eq. (2) follows a modified partial least square known as SIMPLS by Boulesteix and Strimmer (2007); De Jong (1993); Wise (2004) expressed below:

$$\text{Assumption}: X = X_0, Y = Y_0 \textit{ and } t = X_0 w \tag{10}$$

where, $X = X_0$ denotes the centered and scaled matrices of the predictor variables ($RENE, NRENE, RGDP, RGDP^2, ENEE, ENEI$) and $Y = Y_0$ is the centered and scaled matrix of the response variables (CO_2/EF), t and w are the score vector and its corresponding weight vector. X_0 and Y_0 of the centered and scaled matrices of the predictor and response variables are predicted by the PLS method in Eqs. (7–9) through a regression on t.

$$\hat{X}_0/\hat{Y}_0 = tp'/tc', \;\text{ where } p' = \frac{t'X_0}{t't} \text{ and } c' = \frac{t'Y_0}{t't} \tag{11}$$

where, X-loading and Y-loading are vectors p and c; the specific linear combination, $t = X_0 w$ expressed in Eq. (10) has $t = t'u$ as the maximum covariance, and $u = Y_0 q$ as the response linear combination with X-weight and Y-weight (w and q) "*proportional to the first left and right singular vectors of the covariance matrix $X'_0 Y_0$*" (Sarkodie and Owusu, 2017a). The cross-product matrix, $X'_0 Y_0$ is deflated recurrently for the required factors (latent variables) if necessary. The elaborated algorithm is available in Boulesteix and Strimmer (2007); De Jong (1993); Wise (2004).

A SIMPLS model depends on the selection of an optimal number of factors. There is an option to select all factors available during the SIMPLS model estimation, however, the resultant factors may not be optimal to predict the response variables. As such, using a cross-validation method to automate the optimal factor selection was employed. This study used the leave-one-out cross-validation method that prevents overfitting and selects the optimal components by a repetitive leave-out option for a single observation.

Available literature shows that the leave-one-out cross-validation method known as Van der Voet T^2 reports an "*almost unbiased estimator of the generalization properties of the statistical models*" (Cawley and Talbot, 2004; Sarkodie and Owusu, 2017a). The Van der Voet T^2 cross-validation method is a randomization test used to cross-calibrate and simulates the optimal number of latent variables required for the SIMPLS model. The Van der Voet T^2 cross-validation method employs the root mean predicted residual error sum of squares (PRESS) as an indicator for selecting the optimal factors for the model, using the null hypothesis that "*the squared residuals for both models have the same distribution*" (Sarkodie and Owusu, 2017a). The PRESS calculates a value with a minimizing number of factors using the response variables and predictor variables by the estimated SIMPLS model with one Van der Voet T^2 cross-validation method.

3. Results

3.1. Descriptive analysis

Table 2 presents the descriptive statistical analysis of the data series under examination. The descriptive statistical analysis is essential to ascertain the characteristics exhibited by the investigated variables. For the selected period of the data (1974–2013), the minimum carbon dioxide emissions of 172,356 kt occurred in 1974 while its maxima occurred in 2009 at 394,793 kt with an average of 286,673 kt over the

Table 2
Description statistical analysis.

Statistic	CO_2	EF	ENEE	ENEI	NRENE	RENE	RGDP	$RGDP^2$
Mean	286,673	9.3817	10,423.9	1064.42	8440.47	249.3357	29080.3	1.18E + 09
Median	277,946	9.5047	9505.6	911.75	7797.35	250.95	25631.7	6.57E + 08
Maximum	394,793	11.3135	22,989.9	2288.98	16,101.9	338.013	65941.1	4.35E + 09
Minimum	172,356	7.5785	2657.8	345	3487.2	194.4	4389.27	19,265,722
Std. Dev.	66,305	0.8651	5707.02	594.442	3642.76	38.1747	18524.4	1.29E + 09
Skewness	−0.0458	0.0012	0.3341	0.7526	0.3671	0.253	0.5211	1.2045
Kurtosis	1.8616	2.6416	2.071	2.338	2.001	2.0816	2.1774	3.258
Jarque-Bera	2.174	0.2141	2.1826	4.5065	2.5619	1.8326	2.938	9.7824
Probability	0.3372	0.8985	0.3358	0.1051	0.2778	0.4000	0.2302	0.0075*
Correlation								
CO_2	1							
EF	0.5299	1						
ENEE	0.9719	0.5235	1					
ENEI	0.9088	0.4959	0.9445	1				
NRENE	0.9747	0.5304	0.9986	0.9563	1			
RENE	0.8891	0.4516	0.9232	0.8714	0.9194	1		
RGDP	0.9666	0.5330	0.9900	0.968	0.9942	0.8972	1	
$RGDP^2$	0.8828	0.4639	0.9400	0.9732	0.9479	0.8257	0.9685	1
Unit root								
PP								
Level	−2.4640	4.5780	−0.0390	3.0380	1.8180	3.5880	5.8230	−1.1510
Prob	0.1245	1.0000	0.9552	1.0000	0.9984	1.0000	1.0000	0.6944
1st Diff	−8.5700	−9.8910	−7.9940	−7.8100	−6.6250	−10.0430	−7.0350	−8.4610
Prob	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*

* Rejection of the null hypothesis, at 5% significance level.

investigated period. The minimum ecological footprint of 7.58 consumption per capita occurred in 1982 while its maxima occurred in 2003 at 11.31 per capita with a mean of 9.38 per capita. In terms of energy-related services, the minimum exportation of energy occurred in 1975 accounting for 2658 petajoules while its maxima occurred in 2013 at 22,990 petajoules and an average of 10,424 petajoules. The minimum imported energy of 345 petajoules occurred in 1985 while its maxima occurred in 2013 at 2288.98 petajoules and an average of 1064.42 petajoules. The minimum renewable energy produced in Australia occurred in 1979 at 194 petajoules while the maximum production occurred in 2013 at 338 petajoules with an average production of 249 petajoules. The maximum renewable energy production was complimented with growth in wind, solar and bagasse even though there was a decline in hydropower due to rainfall variability (Department of Industry, 2016). The minimum nonrenewable energy produced in Australia occurred in 1974 at 3487 petajoules while the maximum production occurred in 2013 at 16,102 petajoules with an average production of 8440 petajoules. The variation in the production patterns is due to the addition of new coal mining sites to existing energy systems and population increase, thus, increasing energy demand and supply. The minimum economic growth expressed as per capita GDP of AU$ 4389 occurred in 1974 while the maximum per capita GDP of AU$ 65,941 occurred in 2013 with an average per capita GDP of AU$ 29,080.

The skewness statistic reveals that except carbon dioxide emissions, all the remaining data series have a long right tail, thus, positively skewed, however, the kurtosis statistic shows that except the squared of per capita GDP, all the data series exhibit a platykurtic distribution. The Jarque Bera test of the normal distribution as the null hypothesis reveals that, except the squared of per capita GDP, all the data series exhibit a normal distribution at 5% significance level.

The correlation analysis reveals that energy imports and exports, renewable and nonrenewable energy production and economic growth have a strong relationship i.e. as it approaches 1, with carbon dioxide emissions however, there is a weak relationship between ecological footprint and the independent variables.

As a precondition of FMOLS, DOLS, and CCR methods, the data series should be integrated of order one and cointegration prior to the application of the methods. This study employs Phillips-Perron (PP) (Phillips and Perron, 1988) unit root test to examine the integration order of the variables. The PP unit root test in Table 2 reveals that the null hypothesis of a unit root cannot be rejected at level but rejected at first difference, thus, the data series under investigation are integrated of order one.

3.2. FMOLS, DOLS and CCR estimation results

Hansen (Hansen, 1992) proposed the use of Lagrange Multiplier test (Lc) statistic for estimating the parameter instability shown in Table 3. The Hansen's Instability test reveals that the null hypothesis of cointegration cannot be rejected [Lc = 0.7736 at p-value >5% (i.e. 0.1038)].

The predictive power of FMOLS, DOLS, and CCR are 97.8%, 99.8% and 97.8%, respectively, thus, the predictive power of DOLS outweighs both FMOLS and CCR. The DOLS estimator in Table 3 reveals that 1% increase in RENE decreases CO_2 emissions by 0.74%, while 1% increase in NRENE, ENEI and RGDP increase CO_2 emissions by 2.3%, 0.3% and 0.24%, respectively. Dogan and Ozturk (2017) found similar outcomes, however, the only difference is that they considered the role of renewable and nonrenewable energy consumption rather than production.

3.3. SIMPLS model

3.3.1. Estimation results

To corroborate the FMOLS, CCR and DOLS results, this study employed the SIMPLS multivariate method to estimate two models, namely (1) pollution-energy related service-disaggregate energy production and growth nexus and (2) environmental degradation-energy related service-disaggregate energy production and growth nexus by following the environmental Kuznets curve hypothesis pathway.

Table 4 presents the results of the cross-validation method for factor selection. The table reveals a minimum root mean PRESS of 0.6612 corresponding to 5 factors as the minimizing number of components, which are selected as the optimal components for the SIMPLS model estimation. Using the 5 factors, the next step of the SIMPLS model is to analyze the Variable Importance of Projection (VIP) using the approximation of VIP >0.80 (Sarkodie and Owusu, 2017a). The VIP

Table 3
FMOLS, DOLS and CCR estimation results.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FMOLS				
ENEE	−0.1478	0.0621	−2.3806	0.0232
ENEI	0.0151	0.0180	0.8424	0.4056
NRENE	0.1576	0.0872	1.8079	0.0797
RENE	−0.1435	0.0362	−3.9631	0.0004
RGDP	0.3639	0.0256	14.2081	0.0000
C	9.5044	0.2834	33.5390	0.0000
R-sq	0.9795	Adj. R-sq	0.9764	
DOLS				
ENEE	−0.0826	0.1486	−0.5562	0.5917
ENEI	0.3031	0.0407	7.4416	0.0000
NRENE	2.3099	0.2858	8.0830	0.0000
RENE	−0.7382	0.0589	−12.5353	0.0000
RGDP	0.2352	0.0308	7.6477	0.0000
C	−6.3769	1.3066	−4.8805	0.0009
@TREND	−0.0798	0.0047	−16.8304	0.0000
R-sq	0.9980	Adj. R-sq	0.9921	
CCR				
ENEE	−0.0098	0.0715	−0.1366	0.8921
ENEI	0.0480	0.0205	2.3454	0.0252
NRENE	0.0186	0.1072	0.1736	0.8632
RENE	−0.1638	0.0409	−4.0082	0.0003
RGDP	0.3124	0.0189	16.5206	0.0000
C	9.9008	0.3461	28.6102	0.0000
R-sq	0.9796	Adj. R-sq	0.9765	

Cointegration test - Hansen parameter instability

Lc statistic	Stochastic Trends (m)	Deterministic Trends (k)	Excluded Trends (p2)	Prob.*
0.7736	5	0	0	0.1038

estimation is essential to determine the viable candidates for the model. Thus, contrary to unit root test employed by other econometric methods, like FMOLS, DOLS and CCR, to test for first order integration of data series, the PLS models require data series to have a VIP >0.8 on the metric scale, lower than the optimum scale suggests that the data series is not viable for the model estimation, thus, affects the predictive power of the SIMPLS model. Table 5 reveals that all the data series considered in the SIMPLS model are >0.8. Another revelation from Table 5 is that NRENE, ENEE, RGDP and RGDP2 have VIP >1 meaning that the aforementioned data series are highly influential in the model while RENE and ENEI have VIP <1 thus, are moderately influential in the SIMPLS model estimation.

After fulfilling the minimum requirement of the VIP, the next step is the estimation of the relationship between environmental pollution/environmental degradation, energy-related services, disaggregate energy production and economic development while testing for the validity of the EKC hypothesis in Australia. Table 6 presents the results of the SIMPLS model estimation with the corresponding coefficients of the data series. Contrary to the inability of FMOLS, DOLS, and CCR to tame collinearity in the model, thus eliminating RGDP2, SIMPLS corrected the infractions making it possible to estimate the validity of the EKC hypothesis. Both CO_2 emissions and EF estimation results are presented in Table 6. The results reveal that 1% increase in nonrenewable energy production increases EF by 0.26% and CO_2 emissions by 0.47%. Increasing energy imports by 1% increase EF by 0.37% and CO_2 emissions by 0.15%. On the contrary, 1% increase in renewable energy production declines EF by 0.34% and CO_2 emissions by 0.15%. Growing energy exports by 1% decrease EF by 0.99% and CO_2 emissions by 0.16%. On economic development, the results reveal that RGDP is positive while $RGDP^2$ is negative thus, validating the EKC hypothesis in Australia. The economic growth per capita increases Australia's EF and CO_2 emissions by 0.88% and 0.81% and declines thereafter (i.e. -0.5*RGDP/RGDP2) which is contrary to Shahbaz et al. (2017) who revealed no evidence of a U-shaped relationship between CO_2 emissions and economic growth. The diagnostic plots in Fig. 1(a) shows the normal quantile plots of the residuals. The graphical representation shows that the SIMPLS model is normally distributed thus, confirming the independence of the residuals. Table 7 shows that the predictive power of SIMPLS method for CO_2 emissions and EF model is 98% and 35%, respectively. Thus, 98% of variations were explained by the independent variables for the CO_2 emissions

Table 4
Selection of factors and cross-validation test.

№ of factors	Root mean PRESS	Plot	van der Voet T²	Prob > van der Voet T²
0	1.0256		22.2581	<.0001*
1	0.6853		7.3409	<.0001*
2	0.6920		5.2416	0.0420*
3	0.6763		4.1836	0.0750
4	0.6637		2.3361	0.3030
5	0.6612		0.0000	1.0000
6	0.6753		9.7043	0.0030*

Each of the dotted lines represents 0.2 unit.
* 5% significance level.

Table 5
Results of variable importance.

X	VIP	Graphical view
NRENE	1.0160	
RENE	0.9262	
ENEE	1.0199	
ENEI	0.9650	
RGDP	1.0507	
$RGDP^2$	1.0171	

The blue line represents the required VIP of 0.80.

while 35% of variations were explained by the independent variables for the EF model reviewed in Fig. 1(b).

4. Discussion

4.1. Sustainability sensitivity analysis

In the final step of this study, different scenarios are examined that can minimize CO_2 emissions and ecological footprint (EF) while increasing economic development and maintaining an optimal level of nonrenewable energy production and energy-related services. Fig. 2 presents eight different scenarios of sustainability sensitivity analysis. The prediction profiler is used in the SIMPLS model to examine the sensitivity of dynamic changes in the independent variables under investigation. The purple triangle in Fig. 2 denotes the sensitivity indicator which shows the direction of the corresponding value of the partial derivative of the profile function with reference to the current value. It is important to note that the scale of the sensitivity analysis plot is based on 100% points.

To make the scenarios parallel with the sustainable goals by 2030, this study projected Australia's energy demand, non-renewable and renewable energy production, and energy imports and exports using the historical data. Based on the forecasted data, this study estimates the percentage changes from 2014 to 2030. The output is used to estimate the sensitivity of the nexus between CO_2 emissions and ecological footprint, disaggregate energy production and energy-related services.

In Appendix B, the forecast reveals that energy consumption in Australia will reduce by 3.3% in 2030, a reflection of the decline of energy imports in 2030 by 10.4%. On the contrary, energy exports will increase by 34.37% coupled with an increase in renewable and non-renewable energy production by 14.55% and 71.65%, respectively. Thus, Australia's energy consumption in 2030 will be 50.12% of energy production excluding the 35.63% of energy imports by 2030. Using the forecasted changes in Australia's energy sector, the sensitivity of the future changes in CO_2 emissions and environmental degradation, expressed as ecological footprint (EF), can be quantified.

Fig. 2(a) reveals that CO_2 and EF will increase by 2.56% and 21.15% in 2030 assuming no change (business as usual) in NRENE, RENE, ENEE, ENEI and RGDP. Thus, the current energy portfolio coupled with economic development deteriorates the environment and declines environmental quality. As such, other seven scenarios are proposed to examine the sensitivity of the aforementioned variables in the attainment of sustainable development by 2030.

It is assumed in Fig. 2(b) that Australia's energy demand (50.12% of energy production) in 2030 will be met using only fossil fuel energy sources (50.12%) at an economic growth of 3% as proposed by World Bank. Fig. 2(b) reveals that, depending on only fossil fuels, the energy sources will increase CO_2 emissions by 31.55% and EF by 37.79%. On the contrary, Fig. 2(c) assumes that the 2030 energy demand (50.12% of energy production) will be met by only renewable energy sources (50.12%) and all other variables remain constant at an economic growth of 3%. The results show that CO_2 will decline by 1.05%, while EF will increase by 12.47%.

In Fig. 2(d), this study assumes that the 2030 energy demand (50.12% of energy production) will be dependent on fossil fuels (50.12%) coupled with energy exports (34.37%) at 3% economic growth, while all other variables remain constant. The results reveal that this scenario will increase CO_2 by 26.24% and EF will increase by 9.69%.

Fig. 2(e) assumes the energy demand (50.12% of energy production) by 2030 will be met by only renewable energy sources (50.12%) coupled with energy exports (34.37%) in 2030 to ensure 3% annual economic growth. The results reveal that contrary to Fig. 2(d), CO_2 and EF will decline by 6.36% and 15.63%, thus, confirming the empirical results by FMOLS, DOLS, CCR, and SIMPLS models that energy exports and renewable energy sources play a critical role in pollution reduction and sustainable environment evidenced in the Sustainable Development Goal 7.

In Fig. 2(f), it is assumed that Australia's energy demand (50.12% of energy production) in 2030 will be met by renewable energy sources (14.49%) coupled with energy exports (34.37%) and energy imports (35.63%) at 3% economic growth. The results show that CO_2 and EF will increase by 4.74% and 5.01%. This is because Australia's energy import is characterized by only fossil fuels, thus, if the percentage of energy

Table 6
Model coefficients estimation.

Coefficient	EF	Graphical view	CO_2	Graphical view
Intercept	0.0000		0.0000	
NRENE	0.2594		0.4693	
RENE	−0.3410		−0.1481	
ENEE	−0.9909		−0.1455	
ENEI	0.3726		0.1492	
RGDP	2.6878		1.5841	
$RGDP^2$	−1.5347		−0.9825	

Each of the dotted lines represents the length of the coefficient plot.

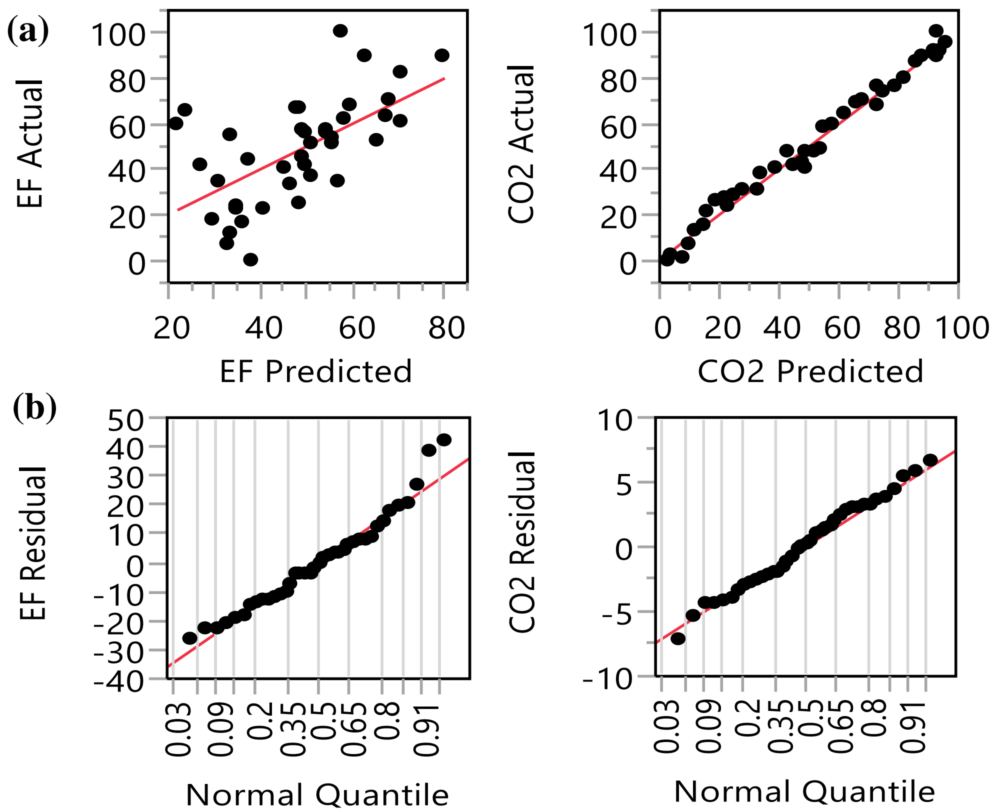

Fig. 1. Diagnostics Plots: (a) Actual by Predicted Plot and (b) Residual Normal Quantile Plot of the SIMPLS model.

imports outweighs renewable energy sources, pollution and degradation will still increase. Fig. 2(g) assumes that Australia's energy demand (50.12% of energy production) in 2030 will be met by renewable energy sources (35.63%) coupled with energy exports (34.37) and energy imports (14.49%) at 3% economic growth. Evidence from Fig. 2(g) reveals that CO_2 and EF will decline by 1.85% and 7.23% when renewable energy sources outweigh energy imports.

Finally, in Fig. 2(h), this study considers all variables in the assumption that fossil fuel energy sources and energy imports are increased by 5% each at 3% economic growth with 40.12% renewable energy sources penetration coupled with 34.37% energy exports. This study reveals that CO_2 and EF will decline by 1.55% and 10.21%.

A decline in CO_2 emissions and EF is dependent on a <5% increase in fossil fuel energy production while economic growth is pegged below 3%. In other words, countries that appear to depend on fossil fuel energy-driven economy will have difficulty to reduce the impacts on environmental quality and sustainability.

This study clearly shows that increasing fossil fuel energy production above 5% coupled with an increase in economic development above 3% accelerates CO_2 emissions and EF, leading to poor environmental quality while reducing environmental sustainability. Decoupling the double burden (i.e. fossil fuel energy production and economic growth) and pegging the rates below the proposed levels will accelerate Australia's effort to achieving the emission target by 2030.

In accordance with Australia's annual GDP growth rate of about 2.6% in 2016 by World Bank (World Bank, 2016a), Fig. 2(h) may be selected as the optimal scenario for environmental sustainability policies. Based on the 2.6% economic growth in 2016, it is assumed that Australia's GDP will increase to around 3%, as such, the decline in CO_2 emissions and EF from the energy sector is dependent on the reduction of the share of fossil fuel energy production while increasing the share of renewable energy production. The share of oil (i.e. crude oil, LPG and refined products) dominated Australia's energy consumption by an increased to 2237 PJ (37.8%), followed by coal consumption at 1908 PJ (32.2%), natural gas at 1431 (24.2%) and renewable energy consumption at 343 PJ (5.8%) (Department of Industry, 2016). It also means that declining CO_2 emissions and EF will not affect economic growth since energy exports will increase to about 20%. In 2014–2015, Australia's energy export increased from 12,509 PJ to 13,088 PJ supported by production growth of coal, natural gas, oil and LPG, and refined products, which constitute almost two-thirds of energy production (Department of Industry, 2016). It appears that Australia's energy production is gradually becoming export-oriented. Thus, trading of fossil fuels rather than utilization in Australia is one of the identified approaches to maintain the economic growth while reducing the domestic environmental impacts.

Table 7
Model comparison summary.

Variable	% variation explained for cumulative X	% variation explained for cumulative Y	Number of VIP > 0.8
CO2	99.99	98.40	6
EF	97.36	34.61	6
Overall	99.99	67.70	6

NB: X denotes independent variables & Y denotes the dependent variables.

4.2. Comparative assessment of the employed econometric models

This study revealed an agreement between the three estimators (FMOLS, DOLS, and CCR), SIMPLS regression and the sensitivity analysis. The coefficients of FMOLS, DOLS and CCR and the SIMPLS regression

showed the same direction for all variables, however, the significance level differs between the models. In terms of predictability, DOLS outweighs FMOLS, CCR and SIMPLS estimation methods, however, in terms of interpretability and versatility for policy formulation, the SIMPLS estimation model is still beneficial. The following evidence emanates from the estimation methods:

- The SIMPLS model revealed that renewable and non-renewable energy production, and energy exports and imports are important variables for estimating CO_2 emissions and EF in Australia.
- Energy-related services are essential in the determination and abatement of CO_2 emissions in Australia. Thus, energy imports worsen CO_2 emissions while energy exports improve environmental quality since major polluting energy sources are exported to other countries, such as China.
- The role of economic development in Australia cannot be underestimated. This study reveals that any structural change in economic growth in the lives of the populace plays a critical role in CO_2 emissions and sustainability. Decoupling energy production from economic growth is seen to be essential in improving energy efficiency while reducing CO_2 emissions and EF.
- Representing energy production rather than consumption in a disaggregated form has provided a more meaningful interpretation of environmental pollution in Australia. Thus, increasing renewable energy penetration into Australia's energy portfolio decreases the

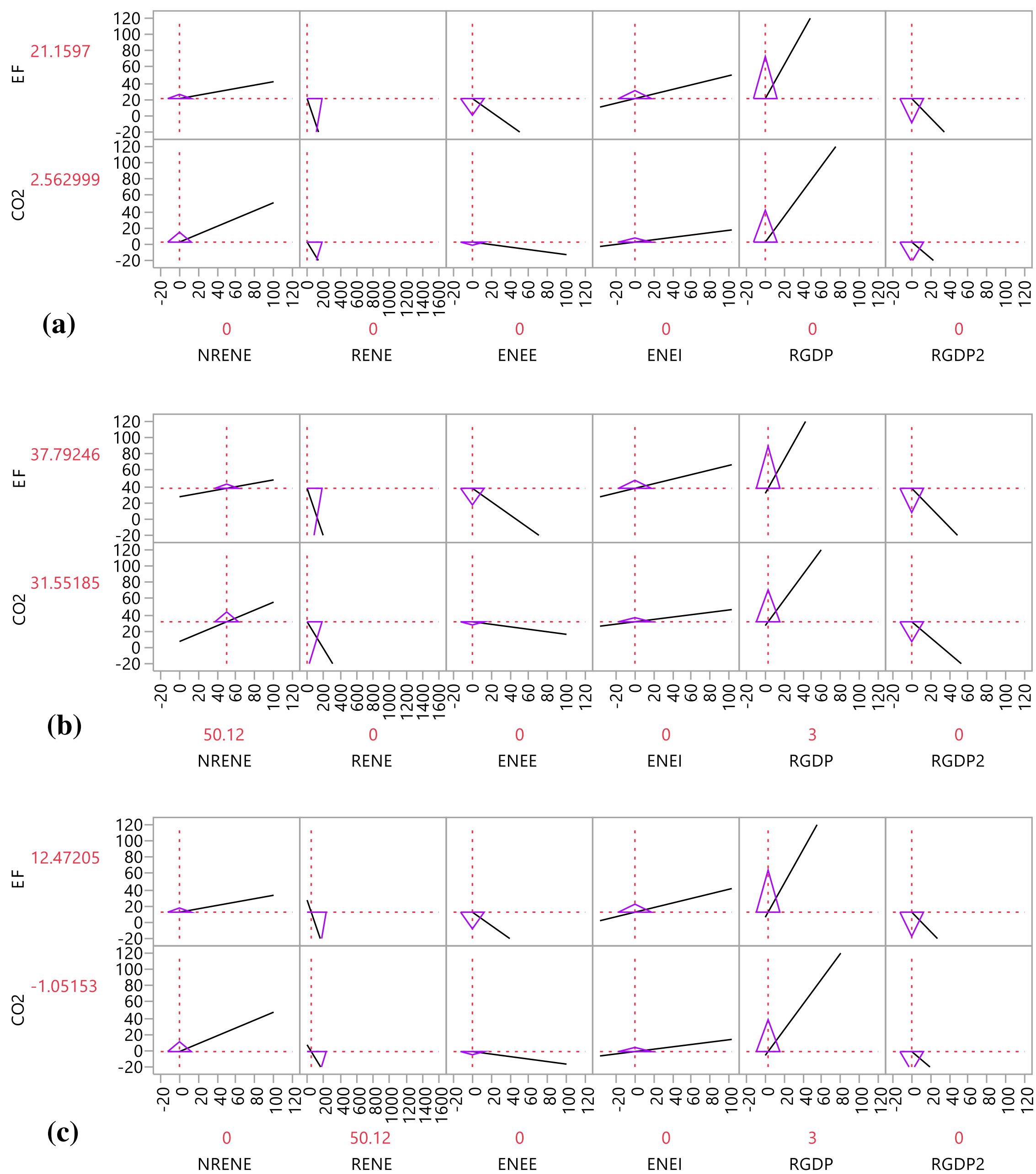

Fig. 2. Sensitivity Analysis: Minimizing Environmental Degradation/Pollution Using (a) Scenario 1 (b) Scenario 2 (c) Scenario 3 (d) Scenario 4 (e) Scenario 5 (f) Scenario 6 (g) Scenario 7 (h) Scenario 8 The purple triangle denotes the sensitivity indicator which shows the direction of the corresponding value of the partial derivative of the profile function with reference to the current value. The values in red are the output of the sensitivity analysis expressed in percentages. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

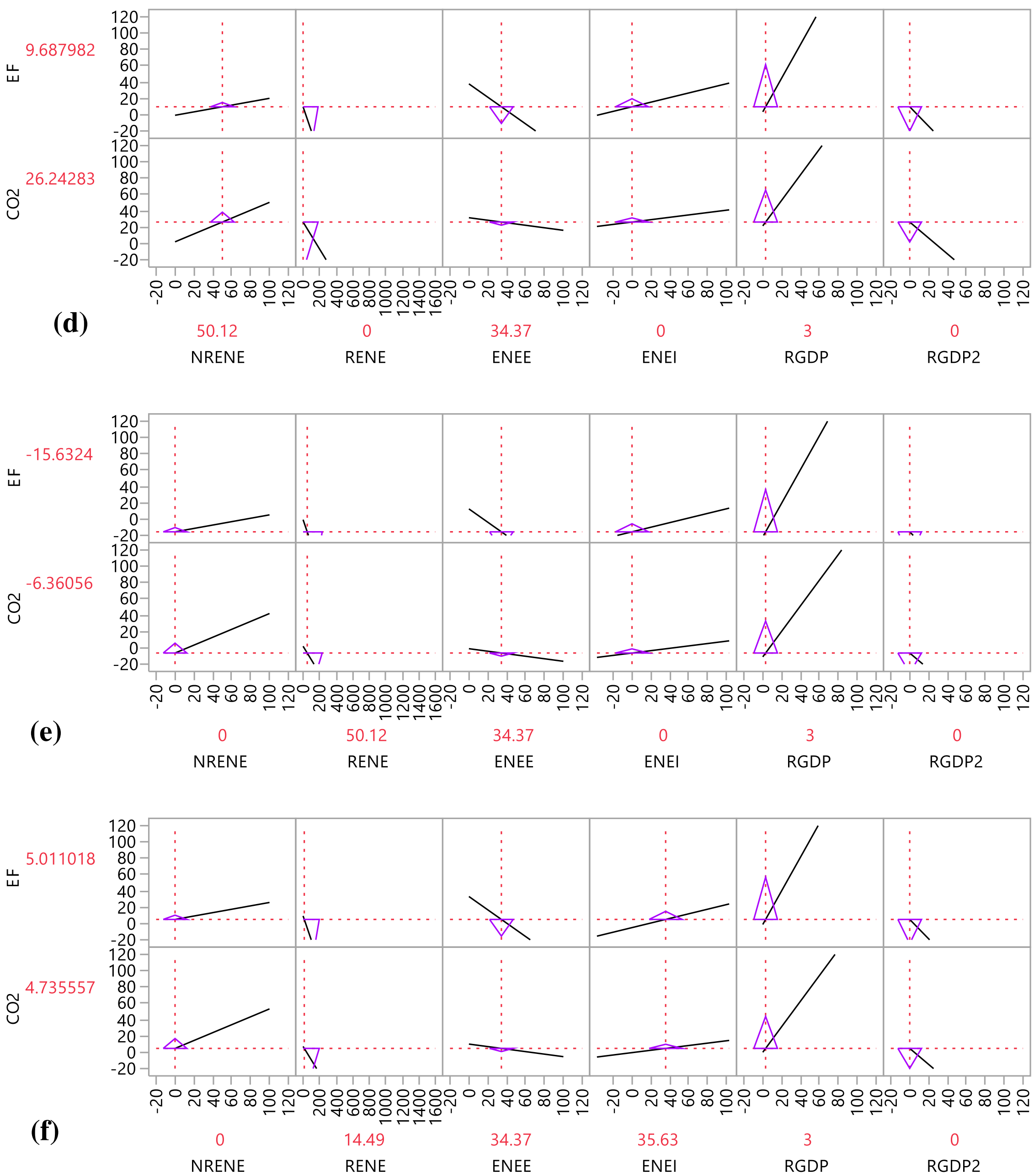

Fig. 2 (*continued*).

levels of CO_2 emissions. On the contrary, increasing the share of non-renewable energy sources in the energy mix increases the levels of atmospheric emissions, thus increasing climate change and its impacts.

The policy implications of the sensitivity analysis are that renewable energy production and energy exports hold the key to the reduction of CO_2 emissions and EF, which contrasts with Australia's current energy portfolio. Renewable energy production accounts for only 2% of the total energy production compared to fossil-fuel energy production which dominates the energy mix (Department of Industry, 2016).

Australia's energy imports comprise of commodities, such as oil and LPG, refined petroleum, natural gas, and coke, which all appear to be nonrenewable energy sources, therefore, increasing the rate of nonrenewable energy import affects the attainment of a clean environment. The sensitivity analysis revealed that nonrenewable energy production above 10% and energy imports above 5% will dampen the goals for the 2030 emission reduction strategies instituted in Australia.

Even though Australia is well endowed with brown coal, black coal, natural gas and uranium, the benefits of incorporating additional renewable energy sources rather than nonrenewable energy sources include increased energy security and diversification of energy supply and reduced natural resource depletion.

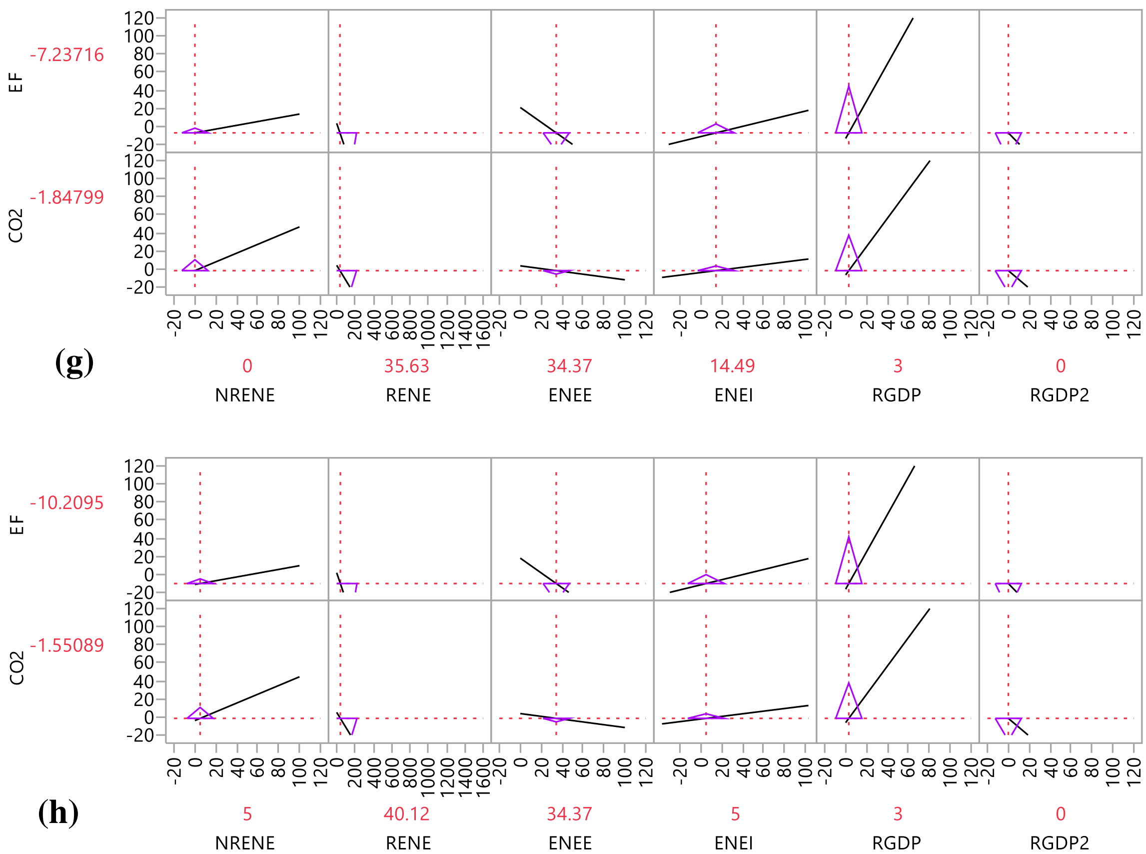

Fig. 2 (*continued*).

5. Conclusion

In this study, the role of Australia's energy portfolio on environmental pollution and environmental degradation expressed as ecological footprint was investigated using locally available data from 1974 to 2013 by applying FMOLS, DOLS and CCR, and SIMPLS regression with a subsequent sensitivity analysis. Contrary to previous studies that employed aggregate energy consumption, this study adopted disaggregate energy production, because in this case energy production is broader (i.e. energy conversion and losses inclusive) and excludes energy imports compared to energy consumption, thus providing the actual empirical evidence necessary for policy formulation and adjustments.

This study revealed that energy-related services, such as energy imports and exports, are essential in the determination and abatement of CO_2 emissions in Australia. Energy imports worsen CO_2 emissions while energy exports improve environmental quality since major polluting energy sources are exported to other countries. Decoupling energy services provide better interpretation of the role of energy sector portfolio in CO_2 emissions and ecological footprint assessment. This study revealed that any structural change in economic growth in the lives of the populace plays a critical role in environmental sustainability. Decoupling energy production from economic growth is essential to improve energy efficiency while reducing CO_2 emissions and environmental degradation. Increasing the share of renewable energy penetration in Australia's energy portfolio decreases the levels of CO_2 emissions, while increasing the share of non-renewable energy sources in the energy mix increases the levels of atmospheric emissions, thus increasing climate change and its impacts. The validity of the EKC hypothesis in Australia means that structural changes in the economy result from a paradigm shift from energy-intensive and carbon-intensive industries to less-energy-intensive and green energy industries and their related services. Finally, this study revealed that Australia's energy portfolio contributes to CO_2 emissions and environmental degradation. As such, structural adjustments are required towards the achievement of a decarbonized economy while meeting the emission targets. The share of renewable energy production in the energy mix needs to be given a priority over non-renewable energy sources and should increase from the current 2% to at least 50%, based on the sensitivity analysis, in order to promote sustainable development, which is in accordance to the sustainable development goals by 2030.

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Declaration

There is no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.05.204.

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